# *Social media, political uncertainty, and the stock market*

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Accepted Version

Fan, R., Talavera, O. and Tran, V. (2020) Social media, political uncertainty, and the stock market. Review of Quantitative Finance and Accounting, 55. pp. 1137-1153. ISSN 1573-7179 doi: https://doi.org/10.1007/s11156-020-00870-4 Available at https://centaur.reading.ac.uk/88906/

# Social media, political uncertainty, and the stock market

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This version: 15th December 2019

## Abstract

This study proposes a new measure of firm-level uncertainty exposure around important political events. More specifically, we construct a degree of (dis)agreement among social media users who jointly mention firms and politicians. We study a sample of over 23 million tweets mentioning both a firm from the S&P 500 composite and 'Trump' from October 2016 to May 2017. We then analyze the relationship between the (dis)agreement measure and individual stock features. The results suggest that increased disagreement among such tweets is associated with heightened stock price volatility and trading volume. This link is observed before the US Presidential Inauguration in January 2017 but not afterwards. The finding is confirmed by further robustness checks based on filtered tweets with policy keywords and policy-sensitive industries.

**Keywords**: Twitter, US Election, stock market, investor sentiment, text classification, computational linguistics

**JEL classification**: D72, G12, G14, L86

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** We thank Cheng-Few Lee (the Editor) and an anonymous referee for their valuable suggestions. We also thank the conference and seminar participants at the 2nd Econometrics and Financial Data Science Workshop and Swansea University for helpful comments. The standard disclaimer applies.

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## Abstract

This study proposes a new measure of firm-level uncertainty exposure around important political events. More specifically, we construct a degree of (dis)agreement among social media users who jointly mention firms and politicians. We study a sample of over 23 million tweets mentioning both a firm from the S&P 500 composite and ‘Trump’ from October 2016 to May 2017. We then analyze the relationship between the (dis)agreement measure and individual stock features. The results suggest that increased disagreement among such tweets is associated with heightened stock price volatility and trading volume. This link is observed before the US Presidential Inauguration in January 2017 but not afterwards. The finding is confirmed by further robustness checks based on filtered tweets with policy keywords and policy-sensitive industries.



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## 1 Introduction

Political events are known to affect stock markets (e.g. Bialkowski et al., 2008; Pastor and Veronesi, 2013; Kelly et al., 2016). This link often arises from the policy uncertainty associated with political events. However, not all stocks are affected by political uncertainty in the same way (e.g. Hill et al., 2019). This work proposes a new measure of firm-level political uncertainty using the agreement among social media users around important political events. Our social media data contain Twitter messages mentioning both a S&P 500 firm name and 'Trump' covering a period around the 2016 US Presidential Election and Trump's Inauguration.

Our study connects several different strands of literature. First, we contribute to the literature about the relationship among politics, policy uncertainty, and stock prices. For example, Pastor and Veronesi (2013) model a relationship between political uncertainty and a stock's risk premium in which the stock price volatility and the risk premium both increase before a change in policy regimes. Baker et al. (2016) and Kelly et al. (2016) provide empirical evidence about an association between policy uncertainty and financial market valuation and price volatility. Notably, the linkage is heterogeneous across industries (Baker et al., 2016). Hill et al. (2019) find varied impacts of political uncertainty associated with the 2016 Brexit Referendum on the UK firms. To the best of our knowledge, there is no prior study utilizing the vast amount of information in social media for firm-level political uncertainty. Our paper furthers previous literature by proposing a new measure of firm-level political sensitivities around the 2016 US Presidential Election based on social media information.

Second, we complement the existing literature on stock forecasts using online social media as a channel for information dissemination. For example, Chen et al. (2014) forecast stock prices using articles and commentaries on an online investor forum. Sprenger et al. (2014b) suggest that there are significant relations between Twitter message features and individual stock returns, liquidity, and volatility.[1] However, prior papers do not use social media information to reveal firms' exposure to political risks. Our paper contributes to this strand of literature by investigating whether social media information mentioning firms and political figures around the 2016 US Election are associated with the same firms' stock movement.

Various data sets are used in the study. First, about 23 million tweets are collected using Twitter streaming application programing interface (API) from October 2016 to May 2017. Prior literature mainly uses secondary Twitter data, but this paper employs primary Twitter data and calculates sentiment measures of tweets, making our Twitter dataset unique. The collected tweets contain a firm name and 'Trump', and we get information about tweets' content and users such as username and ID, date, location, and friend and follower counts. There are 100 companies in our sample, and these firms have 100 or more average daily tweets. Second, daily stock data are acquired from Compustat over two years between 2015 and 2017.

Our investigation is conducted around the 2016 US Presidential Election and Trump's Inauguration in January 2017. We find a negative relationship between the agreement measure, derived from tweets jointly mentioning a company name and 'Trump', and stock price volatility. There is also a similar negative association between the agreement and trading volume. These links are observed before Trump's Inauguration but disappear afterwards. Our investigations account for the mass of Twitter information flows as well as the sentiment embedded in tweets. Furthermore, investigations based on a subsample of tweets with a firm name, 'Trump', and a policy keyword related to 'tax', 'trade', 'job', 'immigration', or 'health care' are performed, and the results confirm our previous findings. Further robustness checks based on subsamples of companies in policy-sensitive industries such as defense, healthcare, and financial services yield even stronger results. These findings indicate that being mentioned

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[1] Several studies focus on other aspects of social media information and stock markets such as emotionality, tone, and mass of information flows (e.g. Bollen et al., 2011; Zhang et al., 2011; Sprenger et al., 2014a). Some other papers use (online) information to investigate the relationship between investor sentiment and stock market (e.g. Li and Yeh, 2011; Ding et al., 2019; Mbanga et al., 2019).

with a political figure around a relevant event potentially increases a firm's exposure to political uncertainty.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the tweets and stock data. Section 4 details the methodology. Section 5 discusses the regression results and robustness checks. Section 6 summarizes the findings and concludes.

## 2 Related literature and hypotheses development

Political uncertainty is a significant determinant of stock performance. However, political risk is not easy to measure, and prior studies have used various models and measures to gauge political uncertainty. For example, Pastor and Veronesi (2013) propose an equilibrium model of government policy choice where stock prices react to political news. In their model, a learning process about political costs/benefits arises before an important change in policy regimes. This learning process generates a risk premium for political uncertainty that heightens stock price volatility. The inputs to the learning process are related to news and debates. Baker et al. (2016) develop a new index of economic policy uncertainty using the frequency of newspaper coverage. Kelly et al. (2016) use information from equity options to price political uncertainty during national elections and global summits. More recently, Hill et al. (2019) examine the heterogeneous impacts of political uncertainty associated with the 2016 Brexit Referendum on UK firms. They use bookmakers' odds to estimate the implied probability of Brexit and firm-level political risk exposure, i.e., Brexit betas.[2] With recent development in internet-based information channels, we add to this strand of literature by utilizing social media

[2] Chunhachinda et al. (2008) reveal that political uncertainty in Thailand is one of the main motives for capital movement from Thailand to the US. Kang and Wang (2018) document that an increase in policy uncertainty can reduce the aggregate earnings in the US. Goodell et al. (2020) find that incumbent party re-election probability is an important determinant of political uncertainty. Xu (2020) show that economic policy uncertainty can increase firms' cost of capital and lower corporate innovation.

information flows as a vehicle to gauge firm-level political risk exposure.

More specifically, we propose a new measure of political uncertainty around an important political event by collecting relevant social media messages mentioning the related political figure and a firm around this change. This is similar in spirit to Cookson and Niessner (2019) who construct a disagreement measure using the sentiment of investors from an online investor platform StockTwits. Particularly, the agreement derived from such messages, i.e., the degree to which Twitter users agree with each other, is under consideration. This is obtained by comparing the number of positive tweets versus negative tweets. The inverse of this measure (disagreement) can be used to assess firm-level political risk exposure because dispersion in beliefs might suggest the level of uncertainty.

Previous research has suggested that higher agreement measures might be associated with higher volatility. For instance, Jones et al. (1994) give empirical evidence that the disagreement among investors in the market can be reflected by volatility.[3] Hence, we would expect higher volatility when the agreement measure among investors is low. Bialkowski et al. (2008) study 27 OECD countries and find that stock market volatility increases during national elections. Boutchkova et al. (2012) show that industries depending more on trade, contract enforcement, and labor have larger volatility when political risks are higher. We now anticipate this relationship when political risk is higher, i.e., before Trump was inaugurated. We propose the following:

**Hypothesis 1:** Agreement is negatively associated with stock volatility.

In addition, prior financial literature argues that investors' heterogeneous beliefs fuel trading volume. For example, Harris and Raviv (1993) and Karpoff (1986) theoretically show that trading volume increases when investors in the market give different opinions about the value

[3] Shalen (1993) reveals that volatility can indicate the difference in opinions among market participants. Banerjee and Kremer (2010) develop a dynamic model that links return volatility and investor disagreement.

of an asset. This evidence is confirmed empirically by Antweiler and Frank (2004) who measure disagreement based on data from online stock message boards.[4] In a more recent and related study, Ge et al. (2019) show that 59 tweets posted by Trump that contain names of public firms around the election and inauguration (when political uncertainty is high) can affect company stock prices, trading volume, volatility, and institutional investor attention. In contrast, we focus on a larger information flow of more than 23 million tweets that jointly mention a firm name and 'Trump' rather than the tweets from Trump. We expect a strong association between agreement and trading volume during high political uncertainty time, i.e., before Trump's Inauguration. Therefore:

**Hypothesis 2:** Higher disagreement among market participants is related to higher trading volume.

Previous literature on the relationship between agreement and stock returns is mixed. For example, Diether et al. (2002) reveal that stocks with higher disagreement in financial analysts' forecasts about earnings have lower stock returns than otherwise identical stocks. Giannini et al. (2019) show that the agreement of opinions of Twitter posts is related to lower earnings announcement returns, and the disagreement in views of tweet messages is linked to higher earnings announcement returns. Therefore, there could be two possibilities regarding the relationship between agreement and stock returns. Moreover, Pantzalis et al. (2000) and Li and Born (2006) reveal that stock market returns are higher before political elections, i.e., when political uncertainty is higher. In one related work, Wagner et al. (2018) find that US firm stock prices react to media news about 'tax', 'trade', 'immigration', and 'health care' around the 2016 US Election when political risk is high. Our approach is different because we focus on stock price reactions to information on social media instead of traditional news articles during

[4] Ajinkya et al. (1991) show empirical evidence that trading volume is positively related to the extent of diverse beliefs of investors. Giannini et al. (2019) find that divergence of investors' opinions in Twitter posts around earnings announcement are related to higher trading volume.

political uncertainty times. We have two hypotheses about the association between the agreement measure and stock returns:

**Hypothesis 3a:** A higher agreement measure is associated with higher stock returns.

**Hypothesis 3b:** A higher agreement measure is associated with lower stock returns.

## 3 Data

We use Twitter API to collect the Twitter data. API can be viewed as a messenger between users and Twitter servers' system. When a user makes requests, the messenger passes them onto the system, and then sends the responses back to the user. In this study, we send requests to collect tweet messages that contain the keyword 'Trump' and a S&P 500 company name. We leave the connections open to collect as many tweets as possible during the harvest periods. Every tweet obtained contains information about the text of the tweet, user ID, user name, and some other fields such as date, source, location, friend counts, follower counts, etc. Tweets are collected from 3rd October 2016 to 5th May 2017 to cover a similar period before and after the 2016 US Presidential Inauguration in 2017.

Daily stock prices for S&P 500 composite firms are obtained from Compustat between 2nd January 2015 and 5th May 2017.[5] We focus on 100 well-known companies that have at least 100 tweets per day on average. We could not obtain satisfactory Twitter data for some companies, e.g. Tiffany, because Trump has a daughter named Tiffany. We try an alternative way using dollar sign followed by the ticker to collect Twitter information, but there is too much noise for some firms, e.g. Ford ('$F'). A full list of the 100 companies used in the study is reported in Appendix A1.

Similar to Fan et al. (2019), we filter and clean the collected tweets in three steps. First, special characters in tweets such as link tokens (starting with 'http', 'https', 'www') are deleted.

[5] We use firms that are included in the S&P 500 as of 2nd January 2015. The reason for using stock data from 2015 is to estimate various measures of expected stock returns, volatility and trading volume.

Second, all tweets with only links or URLs are excluded. Finally, all tweets not in English are eliminated. The remaining sample has about 23 million tweets from 3rd October 2016 to 5th May 2017.

The news sentiment is important information, and thus we separate between positive and negative tweets. We employ a text-processing tool in Python, TextBlob, to obtain a polarity score for every Twitter message. TextBlob will give a polarity score between -1 and 1 for sentiment analysis: a positive score implies positive sentiment, a zero score indicates neutral sentiment, and a negative score suggests negative sentiment. We use both PatternAnalyzer and NaiveBayesAnalyzer in TextBlob to perform sentiment analysis and obtain the same sentiment score for every Twitter message. This adds to the robustness of our analysis. For example, the tweet '@kyleemmi: to everyone who hated on donald trump head line today ford cancels a $1.6 billion mexico plant and adds 700 jobs in michigan' has a polarity score of -0.9 calculated by TextBlob.

## 4 Methodology

### *4.1 Empirical specification and tweet features*

Our regression specification is given as

$$y_t = \alpha + \beta Agreement_t + \delta Positiveness_t + \Upsilon Message_t + \zeta R_t^{Market} + \eta R_{t-1} + u_i + \varepsilon_t \quad (1)$$

Our dependent variables are three market features, i.e. stock returns ($R_t$), volatility ($Volatility_t$), and trading volume ($Volume_t$). The market return, i.e., S&P 500 return $R_t^{Market}$, lagged return, day effects, and firm individual fixed effects are controlled.[6]

We aggregate all daily tweets to investigate the relationship between market features (stock returns, volatility, and trading volume) and the agreement measure of tweets on a daily basis.

[6] We thank the referee for pointing out that the tweets that contain the names of the firms but not 'Trump' could be included as a control variable. However, we leave this for future research due to data availability.

We construct three tweet features: agreement, positiveness, and message volume. Similar to Antweiler and Frank (2004), we define agreement as

$$Agreement_t = 1 - \sqrt{1 - \left(\frac{M_t^{positive} - M_t^{negative}}{M_t^{positive} + M_t^{negative}}\right)^2} \tag{2}$$

$Agreement_t$ captures the degree to which Twitter users agree with each other, i.e., similar or different numbers of positive versus negative sentiment tweets. The agreement measure equals 1 if all messages are positive or negative. The inverse of this measure (disagreement) can be taken as a proxy of the political uncertainty exposure of a firm. Following Sprenger et al. (2014b), we denote positiveness as

$$Positiveness_t = \ln\left(\frac{1 + M_t^{positive}}{1 + M_t^{negative}}\right) \tag{3}$$

where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day $t$; this gives a measure of sentiment as the proportion of positive tweets. We use this measure to control for the sentiment of Twitter messages. We calculate Twitter message volume $Message_t$ as the natural logarithm of one plus the number of tweets from 4:00 pm of the previous trading day to 3:59 pm today. This measure is employed to control for the size of information flows. In line with the opening time of NYSE and NASDAQ (9:30 am to 4:00 pm), we assign the tweet postings after the markets close at 4:00 pm to the next trading day. We separate Twitter messages posted after 4:00 pm because tweets posted after the markets close may only affect stock prices on the following day(s).

[Table 1, Figure 1]

The daily mean is 1,561 for tweets containing 'Trump' and a firm name, and the standard deviations of such tweets are 11,033 postings per day. The large numbers of tweets per firm per day imply that there is sound information content embedded in our dataset. The descriptive statistics of the market and the tweet features are shown in Table 1. Figure 1 plots the number of tweets with the word 'Trump' and a company name around the 2016 US Presidential Election and the Inauguration in 2017 for the 100 firms in our sample. The numbers of tweets are volatile throughout the sample period, and are the highest after the Inauguration in January 2017. There are spikes of positiveness and agreement measures on 2nd of January and 14th of April 2017; the number of 'Trump' tweets are 18 and 100, respectively, and these are the only instances where we have no more than 100 'Trump' tweets. On 16th January 2017, there is another spike in positiveness based on 1,910 tweets containing 'Trump'; nearly all of these (re)tweets contain the word 'deal' or 'trade deal'.

*4.2 Stock indicators*

We use log returns to measure abnormal returns as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

Here, $R_{i,t}$ is log-return for stock $i$ on day $t$, and $E(R_{i,t})$ is expected return. We use two alternatives for the expected return. First, the mean return over the past 100 trading days from day -110 to day -10:[7]

$$AR_{i,t} = R_{i,t} - \frac{1}{100}\sum_{k=10}^{110} R_{i,t-k}$$

However, this simple mean-adjusted return does not reflect the stock's systematic risk; hence, we choose the market model estimated by an ordinary least squares (OLS) regression to estimate the expected return:

$$E(R_{i,t}) = \alpha_i + \beta_i(R_{m,t}) + \mu_i \ \ \forall\, t = 1, 2, \dots, T$$

Term $\alpha_i$ is the intercept, $\beta_i$ relates to systematic risk and measures the association between the stock and the market returns, $\mu_i$ is the error term, and $T$ is the number of periods in the

[7] We also use an alternative 1-year estimation period, i.e. [-10,-260], and obtain quantitatively similar results (available upon request).

estimation period. Following previous literature, we employ a 100-day estimation period starting 10 days prior to the relevant date.[8]

Following Parkinson (1980), we estimate volatility using high and low stock prices $S_{t,high}$ and $S_{t,low}$ on day $t$, and the estimator is given as

$$Vol^{Park} = \frac{\ln(S_{t,high}/S_{t,low})}{2\sqrt{\ln 2}}$$

Trading volume is calculated as the natural logarithm of the number of shares traded on each day.

## 5 Results

### *5.1 Relationship between message volume and market features*

Table 2 suggests that there is a significant and positive correlation between trading volume and the agreement measure of tweets containing the word 'Trump' and a company name. However, this significant correlation is low, which implies that the linear association is relatively weak. The correlations between the positiveness sentiment of tweets containing the word 'Trump' and a company name, and trading volume and returns and are also statistically significant. Moreover, the volume of messages and trading volume are significantly correlated.

[Table 2, 3]

Table 3 reports fixed effects panel regressions of returns, volatility, and trading volume as dependent variables and the agreement measure of tweets containing the word 'Trump' and a firm name as independent variable. We find no significant association between agreement and stock returns across the entire sample period. However, there is a statistically significant and negative relationship between the agreement measure and volatility. This finding reveals heterogeneous impacts of political events on stock volatility channeled through debates on social media. Market participants have diverse reactions to the social media information flows,

[8] Similarly, an alternative 1-year estimation period yields quantitatively similar results (available upon request).

and this may result in more discrepancy in stock valuation (Enikolopov et al., 2018). In particular, small non-institutional investors are more likely to be exposed to noisy information such as Twitter messages. Prior literature (Bialkowski et al., 2008; Boutchkova et al., 2012) also documents higher stock price volatility around national elections.

Moreover, there are statistically significant relations between the agreement measure of tweets containing the word 'Trump' and a company name and trading volume. A 1% increase in agreement with the word 'Trump' and a firm name is related to about 0.009% decrease in trading volume. This confirms our conjecture that more dispersion in investors' beliefs is associated with more trading.

[Table 4]

Given the fact that the tweets in our sample may potentially contain noise, we follow Wagner et al. (2018) and Chen et al. (2019) and filter all Twitter messages with policy keywords. The keywords sets include 'tax cut', 'tax rate', 'tax reform', 'corporate tax', 'zero tax', 'no tax', 'tax avoid', 'tax dodge', 'tax haven', 'tax fraud', 'tax reduc', 'tariff', 'trade war', 'NAFTA', 'renegotiate', 'foreign', 'protection', 'job', 'hire', 'employ', 'border wall', 'immigration', 'healthcare reform', and 'Obamacare'. The regression results based on tweets with 'Trump', a firm name, and a policy keyword are reported in Table 4. Consistent with results in Table 3, there are statistically significant and negative relations between agreement, and stock price volatility and trading volume. A possible explanation is that all Twitter messages about Trump, a company, and a policy keyword can be regarded as rumors about the referred firm and a political figure. Investors have disagreement in their opinions; hence, the agreement measure of tweets is associated with volatility and trading volume.

[Table 5]

In the Pastor and Veronesi (2013) model, the root cause of political uncertainty is that investors digest related news and debates in a Bayesian learning process with noise. This learning process occurs only before an important change in policy regimes. A direct implication is that political uncertainty should significantly reduce after such a regime change takes place. Therefore, we expect that the association between the agreement measure and volatility should weaken significantly after Trump's Inauguration. Table 5 presents fixed effects regressions of returns, volatility, and trading volume as dependent variables and the agreement measure of tweets as independent variable around the inauguration. There are statistically significant relations between the agreement measure of the tweets with the word 'Trump' and a company name, and trading volume and volatility before Trump's Inauguration. However, such associations disappear after Trump was inaugurated as expected. Another potential reason is that, before the inauguration, the Twitter messages about Trump and a company can be treated as speculation about the mentioned firm and the President-elect. Since investors have dispersion in beliefs, the agreement measure based on tweets matters. After the inauguration, such information could be obtained from official sources; hence, it might be treated as noise and only the message volume is relevant.

### *5.2 Robustness checks*

We first examine the lagged relations between tweet and market features by conducting regressions of stock features by a one-day lag of the tweet features. We find no statistically significant relationship between the agreement of lagged tweets and stock returns. However, our results are generally consistent with Sprenger et al. (2014b). There are statistically significant relations between the agreement of Twitter messages with the word 'Trump' and a company name one day ago, and trading volume today.

We then perform further robustness checks by separating the tweet messages into two groups based on the US trading hours: from 4:00 pm yesterday to 9:30 am today as pre-trading, and between 9:30 am and 4:00 pm today as trading. We then repeat the same regressions by using tweet features collected during pre-trading periods. The levels of significance are similar as before.

[Table 6]

Moreover, as Baker et al. (2016) and Boutchkova et al. (2012) point out, the political uncertainty may have a stronger influence on policy-sensitive industries such as defense, health care, finance, and infrastructure construction. Analogously, we identify the sampled companies from these industries to check whether they may be more sensitive to the Inauguration of Donald Trump. This leads to stronger results for firms in these industries (Table 6). This is also consistent with Hill et al. (2019) who find that financial and consumer-facing industries have the biggest exposure to Brexit-related risk.

We finally use alternative risk-factor models in the literature, i.e., Fama-French 3-factor and 5-factor models as a benchmark to calculate the abnormal returns and obtain consistent results. We also use abnormal changes in the volatility measure to obtain robust findings. An abnormal change in the volatility measure equals the volatility today minus the average volatility over the past 100 trading days, i.e. [-110, -10]. A similar measure of abnormal changes in trading volume is also used. There are consistent results for all alternative measures.[9]

## 6 Conclusions

Political uncertainty derived from political events is an important determinant of stock performance (e.g. Pastor and Veronesi, 2013; Baker et al., 2016). Prior literature uses information from traditional news media and the betting markets to gauge political uncertainty. Moreover, previous papers focus on country-level and industry-level political risk exposure. This paper employs information from social media to measure firm-level uncertainty around an important political event. We collect over 23 million tweets that jointly mention a firm and

[9] All results in this section are available upon request.

the keyword ‘Trump’ as a candidate proxy for such measures. Our study explores the relationship between stock features and this measure of political uncertainty exposure because this information dissemination channel can significantly impact stock performance (e.g. Antweiler and Frank, 2004; Chen et al., 2014; Sprenger et al., 2014a, b).

Our findings show that the agreement measure derived from such tweets is associated with stock price volatility and trading volume after controlling for message sentiment and the size of information flows. The impact is statistically significant before Trump’s Inauguration in January 2017. We perform similar analysis for Twitter messages with ‘Trump’, a firm name, and a policy keyword. There are significant relations between the agreement measure and stock price volatility as well as trading volume. We also perform an analysis based on companies from policy-sensitive industries and obtain even stronger results.

There are several implications for academics and practitioners. First, it is important for investors to know that different industries and firms have different exposure to political uncertainty. Thus, they could prepare for the possible impact and act accordingly. Particularly, market participants could manage their exposure to industry-level and firm-level uncertainty when the level of political risk is high. Second, similar political risk measures could be used to gauge a firm’s sensitivity to political uncertainty, especially during a period of important political changes. Given that there are various measures in the literature—and different measures may not capture the same feature—our measure and findings provide a new perspective to investors on the importance of political uncertainty.

## References


Ajinkya BB, Atiase RK, Gift MJ (1991) Volume of trading and the dispersion in financial analysts' earnings forecasts. *Accounting Review* 66(2): 389-401

Antweiler W, Frank MZ (2004) Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance* 59(3): 1259-1294

Baker SR, Bloom N, Davis SJ (2016) Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131(4): 1593-1636

Banerjee S, Kremer I (2010) Disagreement and learning: Dynamic patterns of trade. *Journal of Finance* 65(4): 1269-1302

Bialkowski J, Gottschalk K, Wisniewski TP (2008) Stock market volatility around national elections. *Journal of Banking and Finance* 32(9): 1941-1953

Bollen J, Mao H, Zeng X (2011) Twitter mood predicts the stock market. *Journal of Computational Science* 2(1): 1-8

Boutchkova M, Doshi H, Durnev A, Molchanov A (2012) Precarious politics and return volatility. *Review of Financial Studies* 25(4): 1111-1154

Chen H, De P, Hu Y, Hwang B-H (2014) Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27(5): 1367-1403

Chen S, Schuchard K, Stomberg B (2019) Media coverage of corporate taxes. *Accounting Review* 94(5): 83-116

Chunhachinda P, de Boyrie ME, Pak SJ (2008) Thailand capital flight through trade with the US during times of political and economic instability. *Review of Pacific Basin Financial Markets and Policies* 11(3): 363-387

Cookson JA, Niessner M (2019) Why don't we agree? Evidence from a social network of investors. *Journal of Finance* forthcoming

Ding W, Mazouz K, Wang Q (2019) Investor sentiment and the cross-section of stock returns: new theory and evidence. *Review of Quantitative Finance and Accounting* 53(2): 493-525

Diether KB, Malloy CJ, Scherbina A (2002) Differences of opinion and the cross section of stock returns. *Journal of Finance* 57(5): 2113-2141

Enikolopov R, Petrova M, Sonin K (2018) Social media and corruption. *American Economic Journal: Applied Economics* 10(1): 150-174

Fan R, Talavera O, Tran V (2019) Social media bots and stock markets. *European Financial Management* forthcoming

Ge Q, Kurov A, Wolfe MH (2019) Do investors care about presidential company-specific tweets? *Journal of Financial Research* 42(2): 213-242

Giannini R, Irvine P, Shu T (2019) The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets* 42: 94-120

Goodell JW, McGee RJ, McGroarty F (2020) Election uncertainty, economic policy uncertainty and financial market uncertainty: A prediction market analysis. *Journal of Banking and Finance* forthcoming

Harris M, Raviv A (1993) Differences of opinion make a horse race. *Review of Financial Studies* 6(3): 473-506

Hill P, Korczak A, Korczak P (2019) Political uncertainty exposure of individual companies: The case of the Brexit referendum. *Journal of Banking and Finance* 100: 58-76

Jones CM, Kaul G, Lipson ML (1994) Transactions, volume, and volatility. *Review of Financial Studies* 7(4): 631-651

Kang W, Wang J (2018) Oil shocks, policy uncertainty and earnings surprises. *Review of Quantitative Finance and Accounting* 51(2): 375-388

Karpoff JM (1986) A theory of trading volume. *Journal of Finance* 41(5): 1069-1087

Kelly B, Pastor L, Veronesi P (2016) The price of political uncertainty: Theory and evidence from the option market. *Journal of Finance* 71(5): 2417-2480

Li C, Yeh C (2011) Investor psychological and behavioral bias: Do high sentiment and momentum exist in the China stock market? *Review of Pacific Basin Financial Markets and Policies* 14(3): 429-448

Li J, Born JA (2006) Presidential election uncertainty and common stock returns in the United States. *Journal of Financial Research* 29(4): 609-622

Mbanga C, Darrat AF, Park JC (2019) Investor sentiment and aggregate stock returns: the role of investor attention. *Review of Quantitative Finance and Accounting* 53(2): 397-428

Pantzalis C, Stangeland DA, Turtle HJ (2000) Political elections and the resolution of uncertainty: The international evidence. *Journal of Banking and Finance* 24(10): 1575-1604

Parkinson M, (1980) The extreme value method for estimating the variance of the rate of return. *Journal of Business* 53(1): 61-65

Pastor L, Veronesi P (2013) Political uncertainty and risk premia. *Journal of Financial Economics* 110(3): 520-545

Renault T (2017) Market manipulation and suspicious stock recommendations on social media. *Working paper* IESEG School of Management.

Shalen CT (1993) Volume, volatility, and the dispersion of beliefs. *Review of Financial Studies* 6(2): 405-434

Sprenger TO, Sandner PG, Tumasjan A, Welpe IM (2014a) News or noise? Using Twitter to identify and understand company-specific news flow. *Journal of Business Finance and Accounting* 41(7-8): 791-830

Sprenger TO, Tumasjan A, Sandner PG, Welpe IM (2014b) Tweets and trades: the information content of stock microblogs. *European Financial Management* 20(5): 926-957

Wagner AF, Zeckhauser RJ, Ziegler A (2018) Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. *Journal of Financial Economics* 130(2): 428-451

Xu Z (2020) Economic policy uncertainty, cost of capital, and corporate innovation. *Journal of Banking and Finance* forthcoming

Zhang X, Fuehres H, Gloor PA (2011) Predicting stock market indicators through Twitter "I hope it is not as bad as I fear". *Procedia - Social and Behavioral Sciences* 26: 55-62

**Figure 1** Positiveness, Agreement, and Message measures based on tweets containing the word 'Trump' and a firm name. $Positiveness_t = \ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the counts of positive and negative 'Trump' tweets on day $t$, and $Agreement_t = 1 - \sqrt{1 - \left(\frac{M_t^{positive} - M_t^{negative}}{M_t^{positive} + M_t^{negative}}\right)^2}$. Message are the natural logarithm of the number of tweets containing the word 'Trump' and a company name. Red vertical line represents Inauguration of Trump on 20th January 2017.

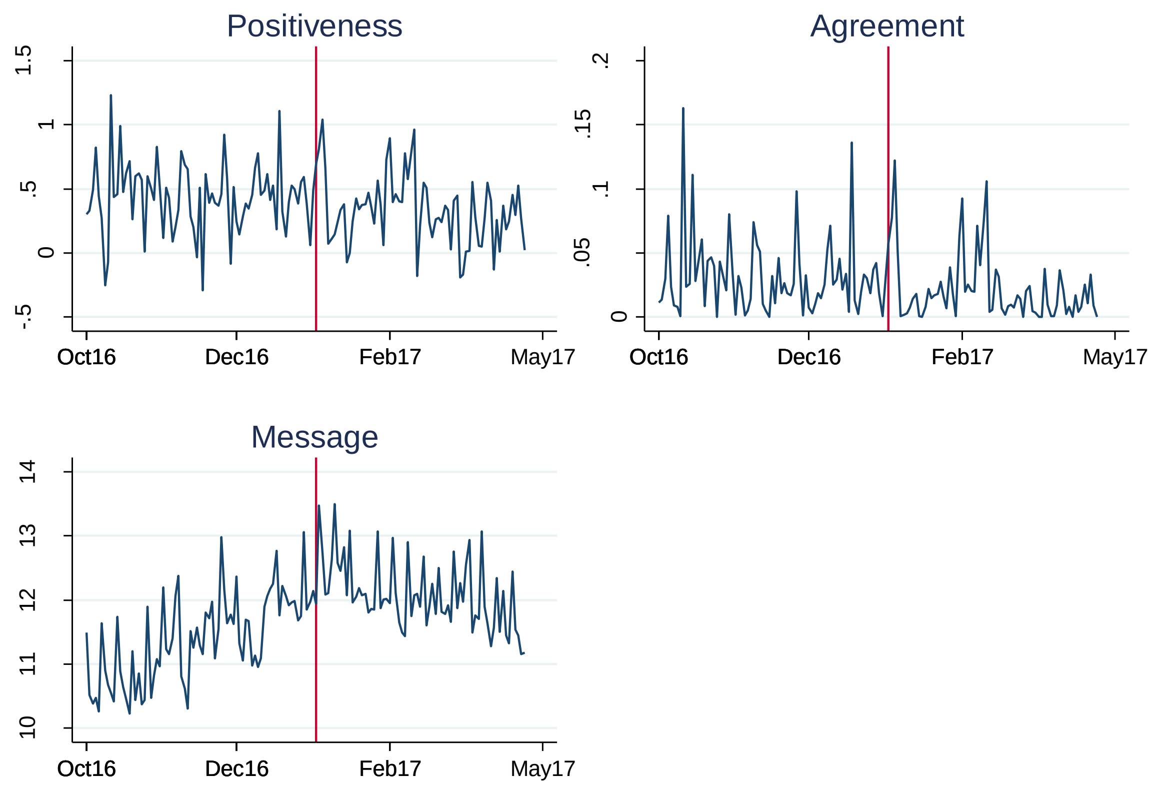

**Table 1** Summary statistics

This table shows the summary statistics of market and tweet features. Returns are log returns, mean-adjusted return is based on a 100-day estimation period i.e. [-110, -10]. Market-model abnormal return is calculated using S&P 500 index. Fama-French 3-factor and 5-factor returns are estimated based on the factors from Kenneth French's website. Volatility is Parkinson (1980) intraday high-low range. All returns and volatilities are reported as percentage points. Message are the natural logarithm of the number of tweets containing the word 'Trump' and a company name. $Positiveness_t = \ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the counts of positive and negative "Trump" tweets on day $t$, and $Agreement_t = 1 - \sqrt{1 - \left(\frac{M_t^{positive} - M_t^{negative}}{M_t^{positive} + M_t^{negative}}\right)^2}$. Full sample size N=14,803 company trading days.

| | Full sample | | Before Inauguration | | After Inauguration | |
|---|---|---|---|---|---|---|
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Market features | | | | | | |
| Return | 0.0671 | 1.5478 | 0.0712 | 1.6325 | 0.0633 | 1.4621 |
| Mean-adjusted return | 0.6693 | 1.5451 | 2.3049 | 1.6266 | -0.8987 | 1.4625 |
| Market-model abnormal return | -0.9344 | 1.4453 | -0.9465 | 1.5111 | -0.9228 | 1.3793 |
| Fama-French 3-factor return | -0.1821 | 1.4285 | -0.1501 | 1.4864 | -0.2127 | 1.3703 |
| Fama-French 5-factor return | -0.1884 | 1.4188 | -0.1557 | 1.4681 | -0.2198 | 1.3692 |
| Market return | 0.0733 | 0.4966 | 0.0682 | 0.5491 | 0.0782 | 0.4404 |
| Volume | 7,084,386 | 13,332,131 | 7,377,316 | 14,677,501 | 6,803,511 | 11,894,370 |
| Volatility | 1.2403 | 0.7420 | 1.3532 | 0.8059 | 1.1320 | 0.6572 |
| Tweet features | | | | | | |
| Message | 1,561 | 11,033 | 1,031 | 6,199 | 2,069 | 14,180 |
| Positiveness | 0.4244 | 1.0633 | 0.4143 | 1.0268 | 0.4341 | 1.0972 |
| Agreement | 0.1230 | 0.1767 | 0.1154 | 0.1722 | 0.1302 | 0.1805 |

**Table 2** Correlations between market and tweet features

This table displays correlations between market and tweet features. Returns are log returns, market return is S&P 500 index return. Volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) volatility using daily high and low prices. Message are the natural logarithm of the number of tweets containing the word 'Trump' and a company name. Positiveness is given as $Positiveness_t = \ln\left(\frac{1+M_t^{positive}}{1+M_t^{negative}}\right)$, where $M_t^{positive}$ and $M_t^{negative}$ are the counts of positive and negative "Trump" tweets on day $t$, and Agreement is $Agreement_t = 1 - \sqrt{1-\left(\frac{M_t^{positive}-M_t^{negative}}{M_t^{positive}+M_t^{negative}}\right)^2}$.* denotes correlations that are significantly different from 0 at the 1% significance level.

| | Return | Market return | Volatility | Volume | Message | Positiveness |
|---|---|---|---|---|---|---|
| Market return | 0.3423* | | | | | |
| Volatility | -0.0594* | -0.0246* | | | | |
| Volume | 0.0050 | -0.0017 | 0.1363* | | | |
| Message | 0.0089 | 0.0249* | -0.0052 | 0.1300* | | |
| Positiveness | 0.0176* | 0.0068 | -0.0029 | 0.0757* | 0.1812* | |
| Agreement | 0.0151 | 0.0109 | -0.0029 | 0.1016* | 0.2257* | 0.4652* |

**Table 3** Regressions of 'Trump' tweets

This table shows associations between 'Trump' tweets and stock performance. The first row displays market features as the dependent variables, and the aggregate measures of 'Trump' tweets are main independent variables. Tweets are collected from 16:00 day -1 to 16:00 day 0. Mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using S&P 500 index return. Volatility is Parkinson (1980) intraday high-low range. Trading volume is the natural logarithm of the number of shares traded. Control variables include market return, lagged stock return, day effects and individual effects. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1) Mean-adj. return | (2) Mrk-model return | (3) Volatility | (4) Trading volume |
|---|---|---|---|---|
| Positiveness | 0.005 | 0.005 | 0.015* | 0.005 |
| | (0.53) | (0.50) | (1.70) | (1.62) |
| Message | -0.021 | -0.020 | 0.054*** | 0.040*** |
| | (-1.38) | (-1.23) | (3.83) | (7.54) |
| Agreement | 0.002 | 0.003 | -0.020** | -0.009** |
| | (0.20) | (0.30) | (-2.13) | (-2.47) |
| Market return | 0.342*** | | 0.010 | 0.014*** |
| | (43.77) | | (1.45) | (5.04) |
| Lagged return | 0.018** | 0.018** | 0.008 | 0.006** |
| | (2.28) | (2.22) | (1.18) | (2.21) |
| No. of obs. | 14,803 | 14,803 | 14,911 | 14,911 |
| $R^2$ | 0.119 | 0.004 | 0.238 | 0.892 |

**Table 4** Regressions of 'Trump' tweets with a policy keyword

This table shows associations between 'Trump' tweets which contain a policy keyword and stock performance. The first row displays market features as the dependent variables, and the aggregate measures of 'Trump' tweets containing a policy keyword are main independent variables. Tweets are collected from 16:00 day -1 to 16:00 day 0. Policy keywords include {'tax cut', 'tax rate', 'tax reform', 'corporate tax', 'zero tax', 'no tax', 'tax avoid', 'tax dodge', 'tax haven', 'tax fraud', 'tax reduc', 'tariff', 'trade war', 'NAFTA', 'renegotiate', 'foreign', 'protection', 'job', 'hire', 'employ', 'border wall', 'immigration', 'healthcare reform', 'Obamacare'}. Mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using S&P 500 index return. Volatility is Parkinson (1980) intraday high-low range. Trading volume is the natural logarithm of the number of shares traded. Control variables include market return, lagged stock return, day effects and individual effects. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1) Mean-adj. return | (2) Mrk-model return | (3) Volatility | (4) Trading volume |
|---|---|---|---|---|
| Positiveness | 0.013 | 0.012 | -0.008 | -0.009** |
| | (1.00) | (0.88) | (-0.72) | (-2.11) |
| Message | 0.022 | 0.024 | 0.055*** | 0.048*** |
| | (1.32) | (1.32) | (3.48) | (8.12) |
| Agreement | 0.012 | 0.013 | -0.020** | -0.013*** |
| | (1.17) | (1.18) | (-2.10) | (-3.58) |
| Market return | 0.343*** | | 0.009 | 0.014*** |
| | (43.03) | | (1.26) | (5.09) |
| Lagged return | 0.017** | 0.018** | 0.010 | 0.007*** |
| | (2.15) | (2.10) | (1.39) | (2.70) |
| No. of obs. | 14,192 | 14,192 | 14,192 | 14,192 |
| $R^2$ | 0.120 | 0.004 | 0.237 | 0.894 |

**Table 5** Regressions of 'Trump' tweets around Inauguration

The dependent variables are mean-adjusted, market-model returns, volatility and trading volume. Columns (1)-(4) reports results for subsample before the Inauguration while columns (5)-(8) are for subsample after the Inauguration. Tweets are collected from 16:00 day -1 to 16:00 day 0. Control variables are market return, lagged stock return, day effects and individual effects. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | Before Inauguration | | | | After Inauguration | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Mean-adj. return | (2) Mrk-model return | (3) Volatility | (4) Trading volume | (5) Mean-adj. return | (6) Mrk-model return | (7) Volatility | (8) Trading volume |
| Positiveness | 0.025* | 0.028* | 0.016 | 0.012** | -0.015 | -0.018 | 0.006 | 0.003 |
| | (1.77) | (1.88) | (1.22) | (2.26) | (-1.12) | (-1.26) | (0.48) | (0.66) |
| Message | -0.028 | -0.031 | 0.088*** | 0.045*** | 0.011 | 0.007 | 0.155*** | 0.063*** |
| | (-1.43) | (-1.46) | (4.63) | (6.12) | (0.37) | (0.23) | (6.09) | (7.04) |
| Agreement | -0.003 | -0.003 | -0.028** | -0.019*** | 0.011 | 0.013 | -0.018 | -0.002 |
| | (-0.20) | (-0.20) | (-1.97) | (-3.40) | (0.71) | (0.81) | (-1.40) | (-0.54) |
| Market return | 0.371*** | | 0.029*** | 0.015*** | 0.305*** | | -0.007 | 0.010*** |
| | (33.48) | | (2.79) | (3.61) | (27.32) | | (-0.75) | (2.76) |
| Lagged return | 0.034*** | 0.038*** | 0.032*** | 0.014*** | -0.016 | -0.018 | -0.022** | -0.002 |
| | (3.13) | (3.21) | (3.15) | (3.50) | (-1.43) | (-1.58) | (-2.25) | (-0.65) |
| No. of obs. | 7,398 | 7,398 | 7,451 | 7,451 | 7,405 | 7,405 | 7,460 | 7,460 |
| $R^2$ | 0.145 | 0.013 | 0.230 | 0.883 | 0.106 | 0.013 | 0.305 | 0.914 |

**Table 6** Regressions of 'Trump' tweets with stocks in policy sensitive industries
This table shows associations between 'Trump' tweets and performance of stocks in defense, healthcare, finance, and infrastructure construction industries. The first row displays market features as the dependent variables, and the aggregate measures of 'Trump' tweets are main independent variables. Tweets are collected from 16:00 day -1 to 16:00 day 0. Mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using S&P 500 index return. Volatility is Parkinson (1980) intraday high-low range. Trading volume is the natural logarithm of the number of shares traded. Control variables include market return, lagged stock return, day effects and individual effects. *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

| | (1) Mean-adj. return | (2) Mrk-model return | (3) Volatility | (5) Trading volume |
|---|---|---|---|---|
| Positiveness | 0.009 | 0.007 | 0.052*** | 0.016** |
| | (0.54) | (0.36) | (2.89) | (2.56) |
| Message | -0.058** | -0.061** | 0.127*** | 0.067*** |
| | (-2.20) | (-2.10) | (4.73) | (7.22) |
| Agreement | -0.020 | -0.018 | -0.035* | -0.016** |
| | (-1.04) | (-0.86) | (-1.80) | (-2.32) |
| Market return | 0.429*** | | 0.010 | 0.019*** |
| | (30.75) | | (0.70) | (3.84) |
| Lagged return | 0.041*** | 0.047*** | 0.049*** | 0.029*** |
| | (2.95) | (3.07) | (3.46) | (5.97) |
| No. of obs. | 4,287 | 4,287 | 4,287 | 4,287 |
| $R^2$ | 0.186 | 0.009 | 0.154 | 0.899 |

**Appendix A**

**Table A1** Sampled companies

This table gives the list of 100 companies employed from S&P 500 as of 2nd January 2015. We could not obtain satisfactory Twitter data for all S&P 500 companies, e.g. Tiffany, as Trump has a daughter whose name is Tiffany. We have tried an alternative way using dollar sign followed by the ticker to collect Twitter information, but we end up with too much noise for some firms, e.g. Ford ('$F').

| | Company | | Company | | Company |
|---|---|---|---|---|---|
| 1 | AES Corp | 35 | Expedia Inc | 68 | Netapp Inc |
| 2 | Aetna Inc | 36 | Exxon Mobil | 69 | Netflix Inc |
| 3 | Allergan Plc | 37 | Facebook Inc | 70 | Newell Brands Inc |
| 4 | American Airlines Group | 38 | Fluor Corp | 71 | Nike Inc |
| 5 | American Express | 39 | Ford Motor | 72 | Nordstrom Inc |
| 6 | Anthem Inc | 40 | Foxconn | 73 | Oracle Corp |
| 7 | Aon Plc | 41 | Gap Inc | 74 | Paypal Holdings Inc |
| 8 | Arconic Inc | 42 | General Electric | 75 | Pepsico Inc |
| 9 | AT&T Inc | 43 | General Motors | 76 | PG&E Corp |
| 10 | Bank Of America Corp | 44 | Goldman Sachs | 77 | Phillips 66 |
| 11 | Bayer AG | 45 | HCP Inc | 78 | Progressive Corp-Ohio |
| 12 | Boeing Co | 46 | Hershey Co | 79 | Raytheon Co |
| 13 | Campbell Soup Co | 47 | Hologic Inc | 80 | Red Hat Inc |
| 14 | Carnival Corp/Plc | 48 | Home Depot Inc | 81 | Scana Corp |
| 15 | Caterpillar Inc | 49 | HP Inc | 82 | Snap-On Inc |
| 16 | CBRE Group Inc | 50 | Humana Inc | 83 | Softbank Group |
| 17 | CBS Corp | 51 | Illumina Inc | 84 | Southern Co |
| 18 | Charter Communications | 52 | Intel Corp | 85 | Staples Inc |
| 19 | Chevron Corp | 53 | Intl Paper Co | 86 | Starbucks Corp |
| 20 | Citigroup Inc | 54 | Intuit Inc | 87 | Stryker Corp |
| 21 | CME Group Inc | 55 | Kellogg Co | 88 | Target Corp |
| 22 | Coach Inc | 56 | Kohl's Corp | 89 | Time Warner Inc |
| 23 | Coca-Cola Co | 57 | Lockheed Martin Corp | 90 | TJX Companies Inc |
| 24 | Comcast Corp | 58 | Loews Corp | 91 | Toyota Motors |
| 25 | Corning Inc | 59 | Lowe's Companies Inc | 92 | UDR Inc |
| 26 | Delta Air Lines Inc | 60 | Macy's Inc | 93 | United Technologies |
| 27 | Devon Energy Corp | 61 | Masco Corp | 94 | Ventas Inc |
| 28 | Disney (Walt) Co | 62 | Mcdonald's Corp | 95 | VF Corp |
| 29 | Dover Corp | 63 | Merck & Co | 96 | Visa Inc |
| 30 | E Trade Financial | 64 | Microsoft Corp | 97 | Vulcan Materials Co |
| 31 | Ebay Inc | 65 | Morgan Stanley | 98 | Wells Fargo & Co |
| 32 | Edison International | 66 | Mosaic Co | 99 | Whirlpool Corp |
| 33 | Equifax Inc | 67 | Nasdaq Inc | 100 | Zimmer Biomet |
| 34 | Equity Residential | | | | |